Analysis of Linear Trends in USA Aiport Temperatures

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I love looking at weather data and have experimented in the past with some of the airport weather station data available from http://www.wunderground.com. I saw this little analysis on R-bloggers https://www.r-bloggers.com/annual-mean-temperature-trends-12-airports/ and thought it would be interesting to look at trends from stations across the US and visualize the results on a map.

```
# Setup, load packages
rm(list=ls())
library(weatherData)
suppressPackageStartupMessages(library(lubridate))
library(ggplot2)
suppressPackageStartupMessages(library(dplyr))
suppressPackageStartupMessages(library(maps))
library(RColorBrewer)
library(magrittr)
library(leaflet)
```

First we need a list of the weather stations we will use. Luckily the weather Data package already contains a compiled data frame 'USAirportWeatherStations' with all the stations and info about them. The 'airportCode' field is what will identify the station when we request the data through the wunderground API.

head(USAirportWeatherStations)

```
##
             Station State airportCode
                                                                    OMW
                                           Lat
                                                   Lon Elevation
## 1
             Central
                         ΑK
                                   PARL 65.57 -144.80
                                                              292 99999
## 2
                Atka
                         ΑK
                                   PAAK 52.22 -174.20
                                                               17 99999
## 3
            Buckland
                         ΑK
                                   PABL 65.99 -161.12
                                                                0 99999
## 4 Portage Glacier
                         AK
                                   PATO 60.79 -148.83
                                                               29 99999
## 5
            Nivalina
                         ΑK
                                   PAVL 67.73 -164.55
                                                                3 70148
                                   PAGL 64.55 -163.05
                                                                8 70199
## 6
             Golovin
                         ΑK
```

I want to fit a long-term trend, so i'll get data starting in 1980 (a lot of the stations seem to go back this far).

```
# Years we will get data for
year_list=1980:2016
st_list <-USAirportWeatherStations$airportCode
# station KMMO 1993 doesn't work, skip
st_list <- st_list[-which(st_list=="KMMO")]</pre>
```

Let's first plot all the station locations. For this analysis, I'll just use those in the continental/lower 48 US states. Including others like Alaska, Hawaii, Virgin Islands etc. makes the map very large and difficult to see. The leaflet pacakee makes a nice interactive map (try zooming and clicking on locations!).

m # Print the map

PhantomJS not found. You can install it with webshot::install_phantomjs(). If it is installed, pleas

The next bit of code downloads the data from http://www.wunderground.com. This is the most time-consuming part of the analysis. It appears that the wunderground API only lets you download a year of data at a time. With my laptop and wifi speed, I estimate it takes about 2-3 sec to download each 1 year data file. For 36 years of data (1980-2016) at about 1600 stations, that works out to about 48 hours! Luckily it is easy to write a loop to do this, and I just let it run overnight or in the background until it was done.

```
# Define function to download daily weather for 1 year.
# I had trouble getting the functions in the weatherData package to work, but once we have the formula
get_yearly_weather <- function (year,st_code){</pre>
        url <- paste0("http://www.wunderground.com/history/airport/",st_code,"/",year,"/1/1/CustomHisto
}
# Define a function to download the weather data for a given station code for each year
get_all_years <- function(st_code){</pre>
        for (i in seq_along(year_list)) {
                year <- year_list[i]</pre>
                savefile<-file.path("~/AirportTemps/Data",paste0("wea",st_code,year,".csv"))</pre>
                if (file.exists(savefile)){
                        print(paste(savefile," already downloaded"))
                }else{
                        url=get_yearly_weather(year,st_code)
                        print(paste("Getting weather data for ",st_code," for year ",year))
                         download.file(url,savefile)
                }
        }
}
# Apply that function to station list to get data for all stations
tryapply(st_list, get_all_years)
```

Ok, we finally have all the yearly data files downloaded. Now i'll combine the yearly files (1980-2015) for each station into a single combined file. I also do some cleaning and remove bad temperature values.

```
# Remove bad temperature values (marked as -99999 in data)
rm_bad_wea_values <- function(dat){</pre>
        dat$Min.TemperatureF[which(dat$Min.TemperatureF==-99999)]<-NA
        dat$Max.TemperatureF[which(dat$Max.TemperatureF==-99999)]<-NA
        dat$Mean.TemperatureF[which(dat$Mean.TemperatureF==-99999)]<-NA
        dat<-subset(dat,Mean.TemperatureF>-50);
        dat<-subset(dat,Mean.TemperatureF<150);</pre>
        dat
}
# Define a function to load and combine all years for a station into one dataframe
combine_years_wea <- function(st_code){</pre>
        savefile <-file.path( "~/AirportTemps/Data",paste0("wea",st_code,"combined.csv"))</pre>
        print(paste("combining years for station ", st_code))
        # Load csv files for each year and combine into a single data frame
        year_list=1980:2015
        dat_all=data.frame()
```

```
for (i in seq_along(year_list)) {
                 year <- year_list[i]</pre>
                 #print(year)
                 dat <- read.csv( file.path( "~/AirportTemps/Data",paste0("wea",st_code,year,".csv")))</pre>
                 dat<-rm_bad_wea_values(dat)</pre>
                 dat$dd <- ymd(dat[,1])</pre>
                 dat_all=rbind(dat_all,dat)
        }
        # Check to make sure we have data (some files are empty)
        if (nrow(dat all)>(20*365)){
                 # Save csv with combined data...
                 write.csv(dat_all,savefile)
        }else{
                 print(paste("station ",st_code," doesn't have data"))
        }
}
# some stations don't work, so need tryapply()
tryapply(st_list, combine_years_wea)
```

Ok, we now have a single file for each station with all the data. I loop through and fit a linear trend vs time for each one, and store all the results in a dataframe. I'll save the trend (coefficient) from the fit, and the p-values to evaluate how reliable the fit was.

```
library(broom)
# save data frame with fit coeffs, p value etc.
temp_fits<-data.frame()</pre>
for (i in seq_along(st_list)) {
        fname<-file.path( "~/AirportTemps/Data",paste0("wea",st list[i],"combined.csv"))</pre>
        if (file.exists(fname)){
                 print(paste("Fitting to ",st_list[i]))
                 dat<- read.csv(fname)</pre>
                 dat$dd <- ymd(dat$dd)</pre>
                 fit1 <- lm(Mean.TemperatureF~dd,data=dat)</pre>
                 fit_tidy <- tidy(fit1)</pre>
#
                  summary(fit1)
                 temp_fits<-rbind(temp_fits,data_frame(airportCode=st_list[i],trend=fit_tidy$estimate[2]
        }else{
                 print(paste("combined file for station ", st_list[i], " doesn't exist, skipping"))
        }
}
# save a csv file with the fit results
write.csv(temp_fits,file.path( "~/AirportTemps/Data", "temp_fits.csv"))
```

Let's look at the results. First i'll define a little function to simplify loading the data.

```
# function to load combined 1980-2016 csv file for specified station
load_combined<-function(st_code){
    fname<-file.path( "~/AirportTemps/Data",paste0("wea",st_code,"combined.csv"))
    dat<- read.csv(fname)
    dat$dd <- ymd(dat$dd)
    dat
}</pre>
```

```
temp_fits <- read.csv(file.path( "~/AirportTemps/Data", "temp_fits.csv"))

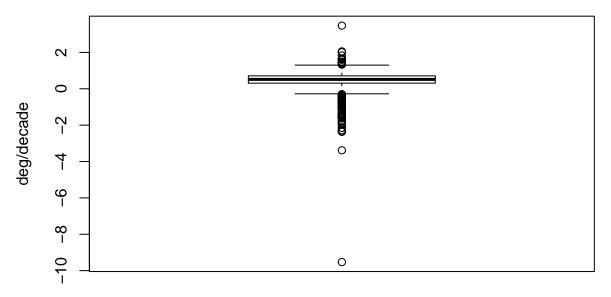
# convert trend to deg/decade
temp_fits$trend <- temp_fits$trend*365*10

How many fits have significant/non sig. p-values?
ig<-which(temp_fits$pval<0.05)
ib<-which(temp_fits$pval>0.05)
print(paste(length(ig), " fits have p-values that are significant(<0.05)"))

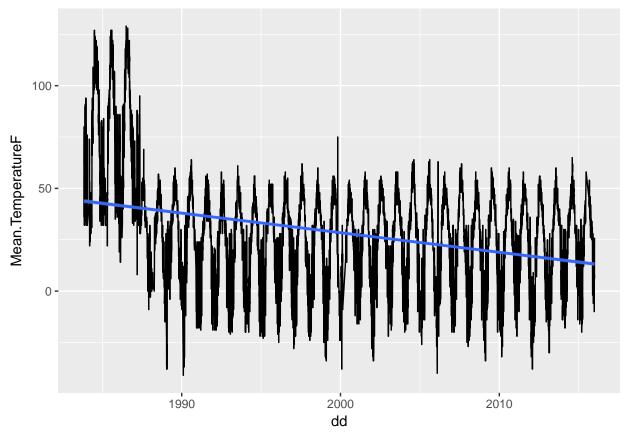
## [1] "674 fits have p-values that are significant(<0.05)"
print(paste(length(ib), " fits have p-values that are not significant(>0.05)"))

## [1] "350 fits have p-values that are not significant(>0.05)"
Look at the distribution of trends.
boxplot(temp_fits$trend[ig],main="Temperature trends",ylab= "deg/decade")
```

Temperature trends



Most of the trends seem reasonable (magnitudes of about 2 degrees per decade), but there a few outliers. Lets look at those and see what's going on.

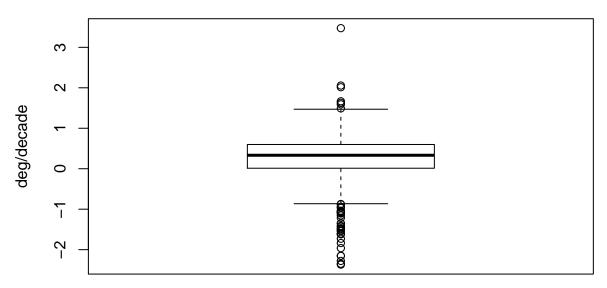


It's obvious from the plot that something is wrong with the data for this station; there is a huge offset after the first \sim 5 years. Maybe the station was moved, or mislabeled? We'll remove this station (note it is in Alaska, so I wouldn't have plotted it in the end anyways).

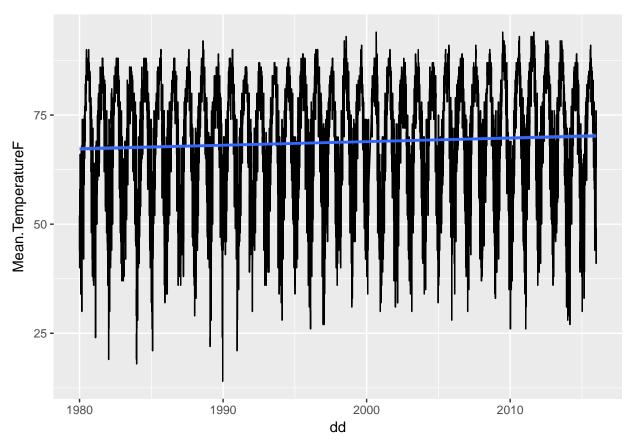
Look at the distribution of trends again with the big outlier removed:

```
boxplot(temp_fits$trend[ig],main="Temperature trends",ylab= "deg/decade")
```

Temperature trends



Let's look at a good fit also, to convince ourselves we are doing this right:



Ok this looks better. Note I haven't removed any of the obvious seasonal cycle. My reasoning is that i'm interested in the long-term trend, and if there is a constant seasonal cycle it should average itself out (ie if the only variability in temperature was a seasonal cycle, the fit should give a trend of zero). In the future I plan to try fits over different time periods, and also with the seasonal cycle removed, to see how that affects the results.

Ok, now it's time to make the awesome map i've been envisioning. First i'll join the fit results with the station info so we have the locations and data together.

```
# Only keep stations with significant p-values
temp_fits_good <- temp_fits %>%
        filter(pval<0.05)
# Join to data frame with station info
results2 <- inner join(temp fits good, USAirportWeatherStations, by="airportCode")
## Warning in inner_join_impl(x, y, by$x, by$y, suffix$x, suffix$y): joining
## factor and character vector, coercing into character vector
# Keep only continental and lower 48 states (map doesn't look good with others)
results2<- results2 %>%
        filter(State!="AK" & State!="MP" & State!="PR" & State!="HI" ) %>%
        arrange(desc(trend))
# Take a look at the largest, smallest trends
#sortdat<-arrange(results2, desc(trend))</pre>
head(results2)
##
       X airportCode
                                                 Station State
                        trend
                                       pval
                                                                 Lat
                                                                         Lon
               KOLF 3.473326 5.393107e-34
```

Wolf Point

MT 48.10 -105.58

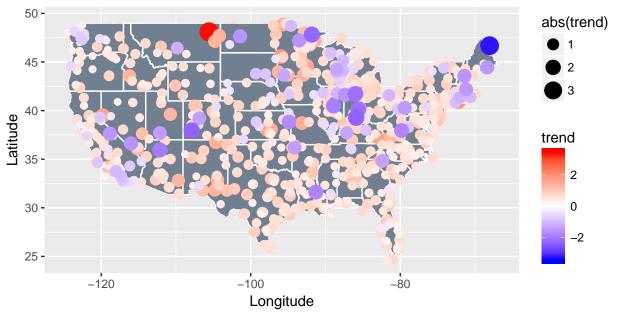
1 575

```
## 2 704
                KHTO 2.013744 4.799912e-44 East Hampton
                                                            NY 40.97 -72.25
## 3 514
                KMOX 1.831821 8.707694e-07
                                                            MN 45.57 -95.97
                                                  Morris
                KRNO 1.666679 7.237582e-38
                                                            NV 39.50 -119.78
## 4 689
                                                    Reno
## 5 366
                KHUT 1.636124 1.180091e-21
                                                            KS 38.07 -97.87
                                             Hutchinson
## 6 522
                KRGK 1.627320 5.429190e-06
                                                Red Wing
                                                            MN 44.58 -92.48
##
     Elevation
                 WMO
           605 99999
## 1
## 2
            55 99999
## 3
           344 99999
## 4
          1341 72488
           470 99999
           239 99999
## 6
tail(results2)
```

```
pval
                                                     Station State
         X airportCode
                            trend
                                                                     Lat
## 650 343
                                                                IN 41.72
                  KEKM -2.152481 5.944056e-38
                                                     Elkhart
## 651 340
                  KAID -2.152536 2.705784e-13
                                                    Anderson
                                                                IN 40.12
## 652 498
                  KELO -2.278304 7.698791e-21
                                                         Ely
                                                                MN 47.82
## 653 182
                  KTEX -2.347279 4.200821e-34
                                                   Telluride
                                                                CO 37.95
## 654 341
                  KBAK -2.369682 1.266927e-24
                                                    Columbus
                                                                IN 39.27
                  KPQI -3.380191 5.686474e-66 Presque Isle
## 655 434
                                                                ME 46.68
##
           Lon Elevation
                            WMO
## 650
        -86.00
                      237 99999
## 651
        -85.62
                      280 99999
## 652
       -91.83
                     443 99999
                    2767 99999
## 653 -107.90
## 654
       -85.90
                     200 99999
## 655
       -68.05
                     146 72713
```

Now I can plot the map, with the size and color of circles proportional to the trends. Red colors indicate positive (warming) trends, and blue colors indicate negative (cooling) trends.

Linear trend [deg/decade] in mean temp., 1980-2016



Conclusions

The map suggests the following conclusions, though more detailed analysis is needed to confirm them.

- The majority of the stations show a warming trend
- Some stations show a cooling trend.
- Qualitatively from the map, it looks like the south/south east is warming at almost all stations.

Future questions

- Is the trend related to latitude?
- Are the fits sensitive to the exact time-range used?
- What does Alasksa look like?